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A Formulation of the Air 6000 Problem from a Joint Systems Perspective

R.J. Staker

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Joint Systems Branch
Electronics and Surveillance Research Laboratory

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ABSTRACT

The Air 6000 Project seeks to provide Australia with a new aerospace combat capability. The need for such a new capability arises from the impending obsolescence of key assets providing Australia's existing aerospace combat capability. The achievement of a high-quality solution to this problem will require support to decision-making for complex systems-of-systems which involve the interests of multiple stakeholder groups. A formulation of the problem, and some possible techniques for its solution are described in this report.

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1 Introduction

The Air 6000 Project seeks to provide Australia with a new aerospace combat capability. The need for such a new capability arises from the impending obsolescence of key assets providing Australia's existing air combat capability. Joint Systems Branch is responsible for studying the design and integration of complex systems that deliver critical military capabilities, particularly those relying on advanced information technology and telecommunications to closely integrate the operation of diverse ADF assets. Since the military equipment and personnel forming such a system may be drawn from several armed services, these are known as Joint Systems. Since the assets in question may often be systems in their own right, it is frequently appropriate to speak of systems-of-systems in this context.

From a Joint Systems perspective, the problem is to bring into being, and to maintain, a sustainable system-of-systems that, to the greatest extent practicable, matches the needs of the warfighters. It is generally difficult to reduce solution "quality" for such a problem to a single measure. What may be of paramount importance in one situation to one user may be of lesser importance in another situation or to another user. This is treated here by basing the quality function on a degree of belief. The belief in question is the belief that a solution option will perform adequately when confronted with a randomly selected demand which it can reasonably be expected to meet. The belief that is used is not that of a single individual, but rather the combined belief of the stakeholders affected by the problem, and of relevant subject matter experts. A suitable belief calculus is used to combine individual beliefs.

It would be a daunting task to make overall, holistic judgements for a complex system-of-systems unaided. On the other hand, a reductive analysis of component parts in isolation would fail to take into account the importance of interactions between components. Fortunately, modelling techniques exist which allow the problem to be subdivided in a natural way that retains the effects of interactions between groups of components.

1.1 General Problem Formulation

The problem may be cast as a classical operations research problem of the form shown by Expression 1.

$$\begin{aligned}&\text{Maximise } Q(x),\\&\text{with respect to } x \rightarrow x^*,\\&\text{subject to } x \in \mathcal{A}.\end{aligned} \tag{1}$$

In Expression 1, x^* is the solution option that results in the maximum value of the quality measure, Q, and $\mathcal{A}$ is the set of allowable solution options. The optimal solution (x^*) sought is a time-phased plan for asset acquisition and divestment over some planning horizon that results in an ongoing system-of-systems meeting the criteria discussed in the introduction. Of course, any such plan needs to be regularly revisited and updated to reflect newly emerging challenges facing the warfighters. The term "asset" is used in a

broad sense here to mean not only physical assets but also their accompanying organisational structures and doctrine. The term "warfighters" is used to refer to the military users and other defence stakeholders. The term "military users" is used to primarily mean operational level commanders rather than asset operators.

In addition to reflecting various operational demands, the quality measure Q needs to be chosen to reflect the subjective preferences of decision-makers and stakeholders. Furthermore, it should incorporate non-functional aspects, such as versatility and adaptability in the face of newly emerging challenges, as well as addressing affordability issues.

The set of allowable solution options, $\mathcal{A}$, is determined by objective constraints that arise from the designs of available systems, the laws of physics, legal requirements and generally agreed limitations, such as, for example, some absolute upper limit on expenditure. Further constraints arise from the initial state of affairs that pertains at the commencement of the plan, and those which it is anticipated should prevail at the end of the plan. Some matters that the work described here addresses are how to select and evaluate the quality measure Q, how to represent problem constraints in a relatively natural form, and, finally, how to solve the resulting optimisation problem effectively and efficiently.

2 Problem Knowledge

To find a good solution to this problem, two principal kinds of problem knowledge are required. These can be categorised as *subjective problem knowledge*, and as *objective problem knowledge.*

2.1 Subjective Problem Knowledge

Subjective problem knowledge is knowledge about how well alternative solution options suit different "users" and other stakeholders. This subjective knowledge may include any kind of solution knowledge about which varying perceptions exist among the stakeholders in the problem. The subjective problem knowledge is used in determining the solution option quality function Q. A solution option may have different utility for different potential users. For example, potential army, navy, and air force users may all have differing needs that should be taken into consideration. Thus, it is necessary to have some means for eliciting this knowledge from such disparate groups of stakeholders and for allowing solution options to be ranked according to their overall combined or joint utility to the users or warfighters. This implies the need for some organisational learning process to enable implicit needs to emerge from interactions between stakeholders and to be captured. A method for facilitating this learning process and for extracting the required knowledge will be briefly discussed in Section 3.2.

2.2 Objective Problem Knowledge

Objective problem knowledge is knowledge on which all stakeholders should be able to agree since it is incontrovertible. This knowledge determines the feasible set $\mathcal{A}$ from which

solution options must be drawn. Some pieces of objective problem knowledge may be of a technical nature, others of a programming nature and yet others of a financial or legal nature. Thus, objective problem knowledge can further be classified into categories such as *asset knowledge, configurational knowledge* and *external constraint knowledge.* In contrast to subjective quality measures, the constraints imposed by these pieces of knowledge are considered to be non-negotiable.

Asset Knowledge Asset knowledge includes knowledge of the assets that are currently in use, how long these may continue to be used, and knowledge of what assets might potentially be acquired in future.

Configurational Knowledge Configurational knowledge is knowledge about how current assets and potential future assets are mutually interrelated and interdependent. An example of a piece of such configurational knowledge is the fact that a solution option that proposes an air launched cruise missile as a strike weapon must also include a launch platform for the weapon.

External Constraint Knowledge External constraint knowledge is knowledge about external limitations that are imposed on solution options. Examples of such knowledge include a maximum cost upper limit, the laws of physics, technical limitations and legal requirements that must be met.

3 Knowledge Representation

It is necessary to have some means for representing problem knowledge before it may be captured and manipulated. The question of how to represent objective problem knowledge will be considered first. Consideration will given to subjective problem knowledge representation later in Section 3.2.

3.1 Representing Objective Knowledge

Clearly, the consistent specification of the constraints implied by the objective problem knowledge could become a difficult matter for a project as complex as Air 6000, were the task to be approached in an *ad hoc* manner. Mathematically speaking, constraints are relations between the allowable values of solution variables. While these relations could be enumerated in a table in a simple case, such a technique quickly becomes impractical for more complex problems. The alternative to tabular enumeration is to express constraints in some implicit form.

The use of formal logic formulæ for this purpose allows objective problem knowledge to be captured in an implicit or *intensional* form that is independent of any particular software implementation. The question then remains as to what form of logic should be employed. Description Logic has been used in the work described here because it allows the natural and modular specification of the constraints on the assets, and because

there is existing work on efficient reasoning algorithms for such logics [7]. In addition, it has a close correspondence with popular object-oriented representations of information, including "frames". As a result, it can readily be applied to reasoning about information that is held in such forms. This is beneficial because others within Joint Systems Branch have been concerned with capturing information about Joint Systems in an object-oriented format in a knowledge repository. (The software tool "Ptech" has been used for this work [11].) Finally, to some people at least, Description Logic has some intuitive appeal!

3.1.1 Description Logic

Description Logic *axioms* introduce "concepts", which are equivalent to sets of individuals, and "roles", which are equivalent to binary relations between individuals. Description Logic axioms can be thought of as similar to Boolean Algebra, which is familiar to electronic engineers, computer scientists and the like. They are especially suitable for representing configurational knowledge. For example, it may be desired to express the fragment of knowledge that a solution to the Air 6000 problem must offer both an air defence capability and a strike capability. Expression 2 shows how this might be stated in the form of a Description Logic axiom. It may be read as: *"A6kSolution is-a AirDefenceCapability and StrikeCapability"*.

$$A6kSolution \sqsubseteq AirDefenceCapability \sqcap StrikeCapability \tag{2}$$

Description Logic *assertions* introduce individuals and binary relations between them. These may be used to represent asset knowledge such as *"the F/A-18 is a conventional aircraft type which has limited range"*, at least in comparison with an F-111, say.

$$\begin{aligned} FA18 &\in ConventionalAircraft \quad (3)\\ (FA18, FA18Range) &\in has\_range \quad (4)\\ FA18Range &\in \neg LongRange \quad (5) \end{aligned}$$

The greek "∈" symbol, which may be read as "in", is used here to indicate that the item on the left-hand belongs to a concept or a role appearing on the right. The right-hand side may be a Description Logic expression resulting in a derived concept or role, or simply the name of a concept or role. In the case of a concept, the left-hand side is an individual, while in the case of a role, it is an ordered-pair of individuals. Here, the role *"has_range"* has been used to link the individual *"FA18"* to the individual *"FA18Range"*, which is asserted not to be a member of the *"LongRange"* concept, the "¬" symbol in front of *"LongRange"*, which may be read as "not", signifying logical negation. Additional axioms, not shown here, would show how the *"ConventionalAircraft"* concept may contribute to an overall solution (*"A6kSolution"*).

Since the meanings of Description Logic expressions are precisely defined, they are suitable for use in conjunction with artificial intelligence-based problem solving techniques. Of these, Constraint Logic Programming is of particular interest because it offers an

effective tool for solving combinatorial problems such as discovering asset combinations that meet the constraints implicitly contained within a set of Description Logic axioms and assertions [14].

Unfortunately, Description Logic is limited in its ability to deal with graduated forms of knowledge such as cost. A solution to this problem is to extend Description Logic, as required, with "concrete domains" such as the domain of integers, the time domain, and so forth, using other forms of logic such as predicate calculus and temporal logic [4]. Naturally, some of the desirable properties of Description Logic are sacrificed when this is done. Concrete domains can help in expressing external constraint knowledge, such as that the total cost of a solution must be below some upper bound. Constraint Logic Programming techniques can also be used to reason about knowledge expressed using such concrete domains, thus maintaining a link between concrete domain and Description Logic reasoning.

3.2 Representing Subjective Knowledge

In the case of subjective knowledge, there is no absolute "true" or "false", there are only degrees of belief held by a particular subject or agent. It is convenient for the present purpose to use Bayesian probability to represent this degree of belief. The theory of Bayesian Belief Networks allows reasoning about beliefs represented in this way to be performed in an efficient manner [8, 10]. Other possibilities for representing degree of belief also exist. Two examples are the Dempster-Shafer theory of evidence and fuzzy sets [6, 13]. However, Bayesian probability appears to be the representation that is best suited to the current purpose, if only because software tools employing this representation are readily commercially available.

Beliefs or opinions about the adequacy of solution options may often be founded on some form of rigorous analysis or experimentation. The results of such analysis or experimentation need to be combined with judgements about how well the assumptions that underlie the analysis or experiment are supported by reality before it is possible to arrive at a valid overall measure of belief.

The question remains of how to elicit the required beliefs from the warfighters about how well alternative solution options meet their combined, joint needs, particularly where this knowledge may only be implicit, and may need to be made explicit before it can be captured. Unfortunately, familiar decision analysis techniques, such as Multi-Attribute Utility methods or the Analytic Hierarchy Process and its variants, usually only treat individual decision-makers operating in isolation [5, 12].

One approach is to extend some of the ideas from soft systems theory, such as the importance of promoting interactive collaboration among stakeholders, and some associated problem modelling procedures, into a method for eliciting the combined joint preferences of groups of stakeholders. In general, it will be necessary to decompose the problem in some way in order to achieve a tractable scope for making judgements. However, this must be done in a way that preserves the holistic properties of the problem. Thus, an artificial hierarchical decomposition of the problem is to be avoided.

An answer might be found based on the notion of Conceptual Models as proposed by

Checkland's Soft System Methodology (SSM) [2, 3]. SSM has the problem stakeholders, or their representatives, collaborate together to produce Conceptual Models consisting of the functions that should be performed by a system (or system-of-systems in this case) to be acceptable to the stakeholders. The Conceptual Models should broadly cover the range of applicable scenarios, rather than being tied to a particular scenario. Allowance is made for alternative view-points, with separate models being developed for each view-point, where necessary. The Conceptual Model functions may then naturally be taken to represent the stakeholders', in this case the joint warfighters', combined needs. The application of such a method could obviously be facilitated by the provision of information technology support for distributed and asynchronous virtual collaboration to avoid the scheduling and geographical location problems associated with the physical meetings that would otherwise be demanded.

Once the Conceptual Model functions have been identified, it is possible to assess how well they are performed by alternative solution options. It is appropriate to perform the assessment using a probabilistic rating scale in this case (*"probably done well"*, *"don't know"*, *"probably not done so well"*) since Bayesian probability is used as the belief measure. A Bayesian Belief Network corresponding to the Conceptual Models may be constructed, and some appropriate qualitative to numeric mapping used to convert the qualitative ratings into numerical probability values. The numerical assessments obtained may then be used to update the belief network to obtain an overall assessment of solution option adequacy. The properties of Bayesian Belief Networks mean that, while a strict hierarchical decomposition of the problem is not required, independence properties that naturally occur in the Conceptual Models may be exploited to improve computational efficiency.

4 Bayesian Problem Formulation

The quality function, Q, used in the Bayesian problem formulation given here is the *likelihood* of a particular solution alternative, given feasibility and user acceptability. In order to evaluate this function, a Bayesian model of the overall acceptability of alternative solution options is first required. Such a model might be derived in the manner described in Section 3.2.

In the first instance, the case of a single problem stage is considered. Attention is subsequently turned to the case of multiple problem stages.

4.1 Asset Configuration

If attention is restricted to a single epoch, the problem can be regarded as a decision-theoretic configuration problem. The objective is to find the feasible asset configuration that best fits the warfighters' articulated needs. This problem can be formulated mathematically as an operations research problem using Bayesian probability of the form shown by Equation 6.

$$\begin{aligned}&\text{Maximise } P(C = c|X_Q = 1, C \in \mathcal{A}),\\&\text{with respect to } c \rightarrow c^*,\\&\text{subject to } c \in \mathcal{A}.\end{aligned} \tag{6}$$

In this formulation, C is a random variable representing the asset configuration, and c represents a particular value that this random variable can take. The symbol X_Q represents a binary-valued random variable that takes the value 1 when the stakeholders are satisfied with the quality of a solution option, and 0 otherwise. The symbol $\mathcal{A}$ represents the feasible set of asset configurations that satisfy the objective constraints. P is a conditional probability distribution giving the likelihood of each particular asset configuration for the stated conditions. The best asset configuration, c^*, is the feasible asset configuration that is most likely to satisfy the warfighters' needs. This form of reasoning, from evidence (that needs are satisfied and constraints are met) to explanation (the best asset configuration) is known as *abduction* [8, Ch. 8]. It would be possible to have X_Q take more than two values, allowing different levels of stakeholder satisfaction to be represented. In general, separate sets of Conceptual Models for the different levels of satisfaction would then be required.

4.2 Migration Path

To select the best migration path, several epochs must be considered together, resulting in a multiple-stage planning problem. Once again, this is a decision-theoretic problem, because a feasible plan that best meets the needs of the warfighters is sought. As before, the problem can be formulated as a mathematical operations research problem using Bayesian probability of the form shown by Equation 7.

$$\begin{aligned}&\text{Maximise } P(\mathbf{A} = \mathbf{a}|X_Q = 1, \mathbf{A} \in \boldsymbol{\mathcal{A}}),\\&\text{with respect to } \mathbf{a} \rightarrow \mathbf{a}^*,\\&\text{subject to } \mathbf{a} \in \boldsymbol{\mathcal{A}}.\end{aligned} \tag{7}$$

In Equation 7, the symbol $\mathbf{A}$ denotes the plan random variable. It is a vector of random variables representing the actions taken at each stage of the plan. The symbol $\mathbf{a}$ represents a particular assignment of actions a_t, $t = 1, \dots, N$ to these random variables. X_Q is a binary-valued random variable indicating whether the plan is of a satisfactory quality to the warfighters, overall. As in Section 4.1, a possible extension would entail having more than two values for this random variable.

The symbol $\boldsymbol{\mathcal{A}}$ denotes the set of feasible plans. A plan is feasible if the asset configuration at each stage t, c_t, is in the allowable set of configurations for that stage, $\mathcal{C}_t$, and if the action taken at each stage is in the set of allowable actions for that stage. It is assumed that the set of allowable actions at each stage, denoted by $\mathcal{A}_t$, is a function

only of the asset configuration that prevails at the beginning of that stage,c_{t-1} . If this function is denoted by a plain $\mathcal{A}$, then $\mathcal{A}_t$ is given by $\mathcal{A}_t = \mathcal{A}(c_{t-1})$. Here c_0 is the initial asset configuration that exists at the start of the problem.

Let $T(a, c)$ denote the transition function that yields the asset configuration that results when an action $a \in \mathcal{A}(c)$ is applied to an existing asset configuration c. Then the set of feasible plans, $\boldsymbol{\mathcal{A}}$, is given by Equation 8.

$$\boldsymbol{\mathcal{A}} = \{(a_1, \ldots, a_n) | T(a_t, c_{t-1}) \in \mathcal{C}_t, a_t \in \mathcal{A}(c_{t-1}), t = 1, \ldots, n\} \tag{8}$$

4.3 Interpreting the Result

It may be possible that a plan that is derived through applying the method that has been described deviates from the expected result. In that case, it is likely to be illuminating to consider how the plan quality model, and hence subjective preference models, would need to be modified to produce the expected result. Such consideration might either show that some significant issues had been overlooked in developing the original quality model, or else, hopefully would be able to convince those concerned that their original expectations were unreasonable. Through iterating such a process, a more thorough understanding of the nature of the implicit warfighter needs should be achievable.

4.4 Best Decision

In an uncertain world, it might be desirable to keep future options as open as possible so that there is the greatest possible chance of being able to execute a good plan even when things do not turn out as originally expected. One way in which this might be done is to decide to take the action that is most likely to be the first action of any good plan. Re-planning would be done at each stage so that each decision is always based on current information and intentions.

The problem of choosing the best immediate action to take can be formulated in the manner shown by Equation 9. The symbols A_1 and a_1 are used to represent the first elements of the vectors $\mathbf{A}$ and $\mathbf{a}$, respectively.

$$\begin{aligned} &\text{Maximise } P(A_1 = a_1 | X_Q = 1, \mathbf{A} \in \boldsymbol{\mathcal{A}}), \\ &\text{with respect to } a_1 \rightarrow a_1^*, \\ &\text{subject to } \mathbf{a} \in \boldsymbol{\mathcal{A}}. \end{aligned} \tag{9}$$

5 A Solution Technique

A solution technique based on standard Bayesian Belief Network algorithms has been developed for the problems that have been introduced in sections 4.1, 4.2 and 4.4. In

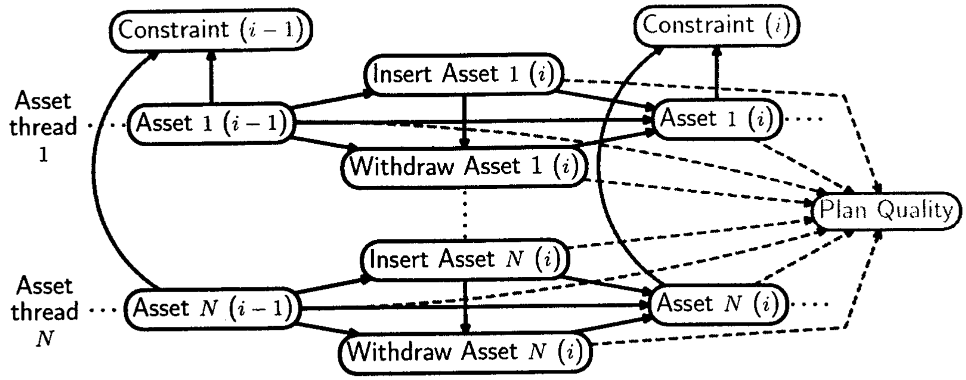

Figure 1: Belief Network Form for Migration Path Planning

the case of the multiple-stage planning problem of Section 4.2, the potential exists for combining Bayesian Belief Network methods with dynamic programming methods, which might be more efficient than using Bayesian Belief Network algorithms alone [1]. However, this is only possible if the quality function has the special form required by the dynamic programming method. In general, this may not be the case, and hence the use of dynamic programming will not be considered any further here.

Attention will be focused on the migration path problem since the configuration problem is a degenerate case of it, and the best decision problem is a variation of it. In solving for the migration path, the plan is represented as several parallel threads, one for each asset. These threads each consist of a series of random variables, alternately representing possible elementary actions on assets (*"insert"* or *"withdraw"*) and the asset conditions (*"in use"* or *"not in use"*) that result. The elementary actions for each stage combine to form the composite action for that stage. The term "action" that has been used elsewhere refers to this composite action, rather than the individual elementary actions.

Figure 1 shows the form of the belief network used. Two successive epochs or stages numbered $i-1$ and i are shown. If there are N assets to be considered, then, in general, there will be N asset threads. A thread need not persist throughout all stages if it is known that the asset cannot be present prior to a certain stage, or after some stage. Such amendments of the general network form allow constraints like these to be incorporated in a convenient and a natural way.

In addition, there are dependencies between asset condition variables and asset action variables, and between asset action variable and asset action variable, as represented by the arrows in the diagram. These dependencies correspond to constraints that ensure that only assets that are currently in use can be planned to be withdrawn, only assets that are not currently in use can be inserted, and that an asset cannot be both inserted and withdrawn at the same time. These general constraints are applicable to any planning problem. Other problem-specific constraints are represented by the deterministic variable nodes *Constraint* (i), *&c.* These correspond to degenerate random variables that take some particular value (in this case *"satisfied"* or *"not satisfied"*) with probability 1.0, depending on the values of the conditioning variables.

It should be emphasised that neither the constraint nodes nor the plan quality node

need to be a single node. They may be belief networks in themselves. In fact, the plan quality node will, instead, generally be a belief network model derived from the warfighters' needs in the way that was outlined earlier in Section 3.2. Conditional probability tables for the constraint variable nodes may be computed from the Description Logic axioms representing objective problem knowledge. Alternatively, Description Logic expressions could be directly translated into corresponding belief networks themselves.

The solution procedure involves constructing a Bayesian Belief Network that represents the plan, constraints and quality model. Then, well-known algorithms are used to incorporate "evidence" that the constraints are satisfied and that the plan quality is adequate into the belief network, and to solve for the Most Probable Explanation. The result is the best plan as obtained by Bayesian abductive inference.

It is possible to have several equally good plans when the quality function is relatively undemanding. Either, one may be selected at random, or the problem may be refined so that only a single best plan results.

5.1 Example

Figure 2 shows an example of a migration plan that has been derived using the process described in the previous section. The assumptions used here are arbitrary ones. They are only used to provide a simple demonstration of the method, and it is not intended that any valid conclusions should be drawn from the results. The solution technique that is demonstrated solely uses algorithms that are available as part of a general purpose Bayesian Belief Network software package.

The demonstration problem is loosely based on the Air 6000 problem. It divides the problem into a number of time periods and asserts sets of constraints that must be satisfied for each of these. Decisions are to be made about when to phase the current F-111 and F/A-18 assets out and when to introduce new assets. The new assets assumed to be potentially available are a stand-off strike weapon (SOW) that could be used with the existing aircraft types to enhance their survivability, a refueller aircraft, a new combat aircraft, which like the old F/A-18 aircraft type would require a refuelling capability for long-range strike, but which would not require stand-off weapons to be survivable, and a conventional air-launched cruise missile system (CALCM). In addition, it has been assumed that the old aircraft types must be retired by the end of period 2. A fully developed problem formulation would also emphasise the phasing of Command and Control, Surveillance and other C4ISR assets, something that has not been considered in this simple example.

There are a number of possible actions that are available to be taken in each time period. The set of possible actions is not necessarily the same for each time segment. Examples of elementary actions are *"Withdraw F-111"* and *"Insert CALCM"*. The overall actions for each stage are a combination of such elementary actions. The problem-specific constraints represented by the constraint nodes enforce the progressive achievement of asset configurations that meet increasingly stringent objective system-of-systems requirements. For the first period, the requirement is simply to maintain the existing strike capability, while for the second it is to maintain the strike capability and increase survivability to at least the level provided by the use of the stand-off strike weapon. For the

third and fourth periods, a higher level of survivability is demanded, such as might be provided through the use of the new aircraft type, or the use of the conventional air-launched cruise-missile system.

In addition to the asset configuration constraints, hypothetical preferences about the plan to be produced have also been expressed using Bayesian probability techniques. These preferences are based on a very simple "cost" metric, which is simply the sum of the number of assets in use and the number of assets being inserted. Some preference distributions for the "cost" of each time segment have been postulated. From this information and the constraints, the "best" plan satisfying the constraints may be obtained through applying a Most Probable Explanation algorithm.

More elaborate preference structures than those used here could easily be represented, and the effects of uncertainties could also be included. In a fuller application of the method, these preference structures would be derived using the methods described in Section 3.2. Also, in a fully developed application of the method, the constraint node conditioning tables would be derived using the Description Logic techniques described in Section 3.1. For this simple example, it was possible to generate the table values using the simple logical expressions directly supported by the Bayesian Belief Network software package that was employed. However, a Description Logic representation was developed first.

Figure 2 shows some output produced from the commercially-available Bayesian Belief Network software package that was used ("Netica") [9]. It shows the plan network, constraint nodes and cost nodes. Attached to these nodes there are tables representing constraints and preferences in probabilistic form. Most of the probability values are 0, 1.0 or *"impossible"*. Values different from these are only required for expressing warfighters' preferences or value systems. The "best" plan has been found by using the Most Probable Explanation feature of the software package.

It should be noted that the example shown here is solely concerned with maintaining a deep air strike capability. The results would obviously be much different for a balanced air defence and strike capability. The results presented in Figure 2 should be read in the following way. The Most Probable Explanation is that obtained by taking each action random variable value to be the one which has the 100% bar beside it. If there is more than one such bar for an action random variable, there are alternative plans that are equally good. There are a number of equally good plans for this example. This is because the preference structure for the costs that has been used is indifferent to costs below a certain figure, and then rapidly becomes unfavourable above this figure. These alternative plans can be manually discovered using the software package by repeatedly setting variables to have one of the alternative 100% values until no such alternatives remain. Of course, in a fully developed system, this process would be performed under software control. Some equally good alternatives have been manually selected so that a unique plan is shown in Figure 2.

6 Future Work

The next step in applying this method is to begin to capture some of the subjective and objective knowledge relevant to the Air 6000 problem in the required form. Once this

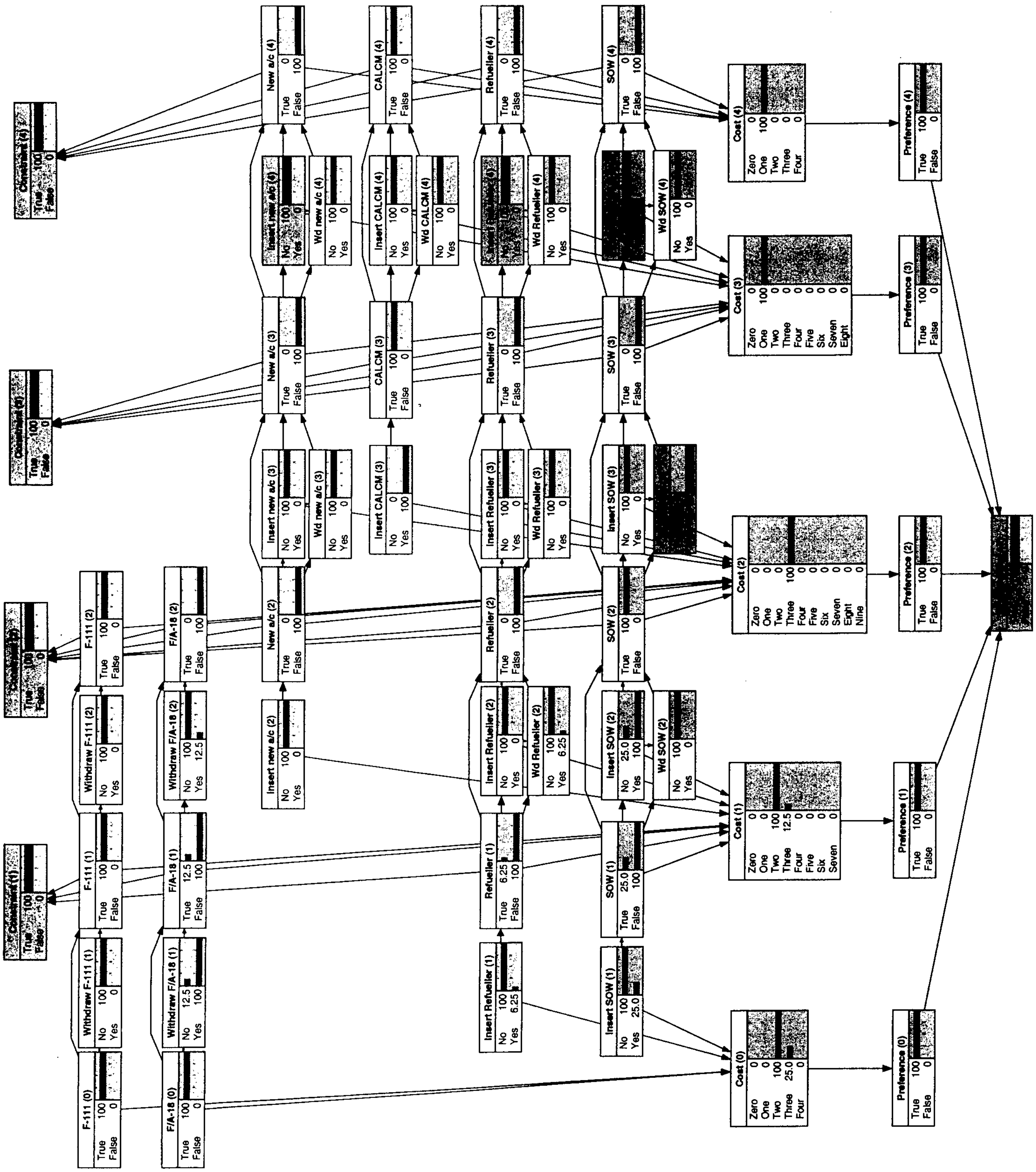

Figure 2: Migration Path Planning Example

has been done, it will be possible to examine the kinds of solutions that that knowledge implies. It is important to realise that not only air assets are important in this problem. C4ISR assets, as well as land and sea assets, must all be taken into consideration.

A longer-term objective may be to develop a software aid that is specifically tailored to support the method that has been described. This aid would facilitate the capture of new and amended knowledge, allow alternatives to be explored and decision recommendations to be rapidly updated.

7 Conclusion

In conclusion, this report has presented a decision-theoretic planning method for addressing complex system-of-systems problems such as the Air 6000 problem. The next step, for the immediate future, is to gather real knowledge from the warfighters and domain experts and to validate the concept more thoroughly using this knowledge base. The development of special purpose software for supporting the method is a longer term possibility. In addition to the application described here, some of the ideas presented may also be of use in other related areas, such as military operations planning and similar planning under uncertainty applications.

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19. ABSTRACT

The Air 6000 Project seeks to provide Australia with a new aerospace combat capability. The need for such a new capability arises from the impending obsolescence of key assets providing Australia's existing aerospace combat capability. The achievement of a high-quality solution to this problem will require support to decision-making for complex systems-of-systems which involve the interests of multiple stakeholder groups. A formulation of the problem, and some possible techniques for its solution are described in this report.

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ELECTRONICS AND SURVEILLANCE RESEARCH LABORATORY
PO BOX 1500 SALISBURY SOUTH AUSTRALIA, 5108
AUSTRALIA, TELEPHONE (08) 8259 5555